MINI PROJECT 2

Problem Statement: - Build a machine learning model that predicts the type of people who survived the Titanic shipwreck using passenger data (i.e. name, age, gender, socio-economic class,etc.).

Objective: Students should learn to build a machine learning model.

Theory:

Here's a step-by-step guide on how to approach this problem using Python and some popular libraries:

1. **Data Collection and Understanding**:
   - Start by obtaining the Titanic dataset, which contains passenger information and survival labels. You can find datasets on websites like Kaggle.
2. **Data Pre-processing**:
   - Clean the data by handling missing values, outliers, and redundant features.
   - Perform feature engineering to create relevant features or transform existing ones.
   - Encode categorical variables into numerical format using techniques like one-hot encoding.
3. **Data Splitting**:
   - Split your dataset into a training set and a test set. This allows you to evaluate your model's performance on unseen data.
4. **Select a Machine Learning Algorithm**:
   - Choose a classification algorithm suitable for this problem. Common choices include Decision Trees, Random Forests, Logistic Regression, Support Vector Machines, or Gradient Boosting.
5. **Model Training**:
   - Fit your chosen algorithm to the training data. The model learns patterns from the data.
6. **Model Evaluation**:
   - Evaluate your model's performance using metrics like accuracy, precision, recall, F1-score, and the ROC-AUC score. Cross-validation can help in assessing how well the model generalizes to new data.
7. **Hyperparameter Tuning**:
   - Experiment with different hyperparameters to optimize your model's performance. Techniques like grid search or random search can be helpful.
8. **Model Interpretation**:
   - Understand the feature importance or coefficients of your model to interpret how different features affect survival.
9. **Prediction**:
   - Use your trained model to make predictions on new, unseen data or the test set.
10. **Post-processing**:

- You may need to further process the model's output, such as setting a threshold for classification.

Importing the Libraries

```
# linear algebra
import numpy as np

# data processing
import pandas as pd

# data visualization
import seaborn as sns
%matplotlib inline
from matplotlib import pyplot as plt
from matplotlib import style

# Algorithms
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.naive_bayes import GaussianNB
```

Getting the Data

```
test_df = pd.read_csv("test.csv")
train_df = pd.read_csv("train.csv")
```

Data Exploration/Analysis

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

The training-set has 891 examples and 11 features + the target variable (survived). 2 of the features are floats, 5 are integers and 5 areobjects. Below I have listed the features with a short description:

survival: Survival

```
PassengerId: Unique Id of a passenger.
pclass:    Ticket class
sex:    Sex
Age:    Age in years
sibsp: # of siblings / spouses aboard the Titanic
parch: # of parents / children aboard the Titanic
ticket:  Ticket number
fare:   Passenger  fare
cabin:    Cabin number
embarked:    Port of Embarkationtrain_df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Above we can see that **38% out of the training-set survived the Titanic**. We can also see that the passenger ages range from 0.4 to 80. Ontop of that we can already detect some features, that contain missing

values, like the „Age" feature.

```
train_df.head(8)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
[illegible]	[illegible]	[illegible]	[illegible]	[illegible] Harris	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S

From the table above, we can note a few things. First of all, that we **need to convert a lot of features into numeric** ones later on, so that the machine learning algorithms can process them. Furthermore, we can see that the **features have widely different ranges**, that we will need to convert into roughly the same scale. We can also spot some more features,that contain missing values (NaN = not a number), that wee need to deal with.

Let’s take a more detailed look at what data is actually missing:

```
total = train_df.isnull().sum().sort_values(ascending=False)
percent_1 = train_df.isnull().sum()/train_df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1,
keys=['Total','%'])
missing_data.head(5)
```

	Total	%
Cabin	687	77.1
Age	177	19.9
Embarked	2	0.2
Fare	0	0.0
Ticket	0	0.0

The Embarked feature has only 2 missing values, which can easily be filled. It will be much more tricky, to deal with the „Age“ feature, which has177 missing values. The „Cabin“ feature needs further investigation, but it looks like that we might want to drop it from the dataset, since 77 % of it are missing.

```
train_df.columns.values
array(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object)
```

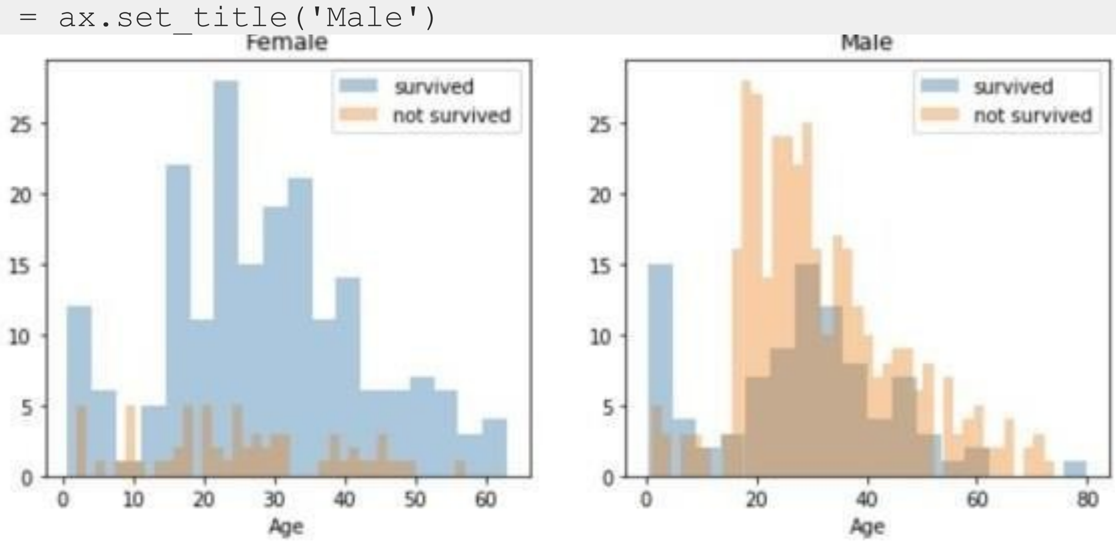
Above you can see the 11 features + the target variable (survived). **Whatfeatures could contribute to a high survival rate ?**

To me it would make sense if everything except „PassengerId“, „Ticket“ and„Name“ would be correlated with a high survival rate.

1. Age and Sex:

```
survived = 'survived'
not_survived = 'not survived'
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(10,
4))women = train_df[train_df['Sex']=='female']
men = train_df[train_df['Sex']=='male']
ax = sns.distplot(women[women['Survived']==1].Age.dropna(), bins=18,
label = survived, ax = axes[0], kde =False)
ax = sns.distplot(women[women['Survived']==0].Age.dropna(), bins=40,
label = not_survived, ax = axes[0], kde =False)
ax.legend()
ax.set_title('Female')
ax = sns.distplot(men[men['Survived']==1].Age.dropna(), bins=18, label
= survived, ax = axes[1], kde = False)
```

```
ax = sns.distplot(men[men['Survived']==0].Age.dropna(), bins=40, label
= not_survived, ax = axes[1], kde = False)
ax.legend()
_ = ax.set_title('Male')
```



You can see that men have a high probability of survival when they are between 18 and 30 years old, which is also a little bit true for women butnot fully. For women the survival chances are higher between 14 and 40.

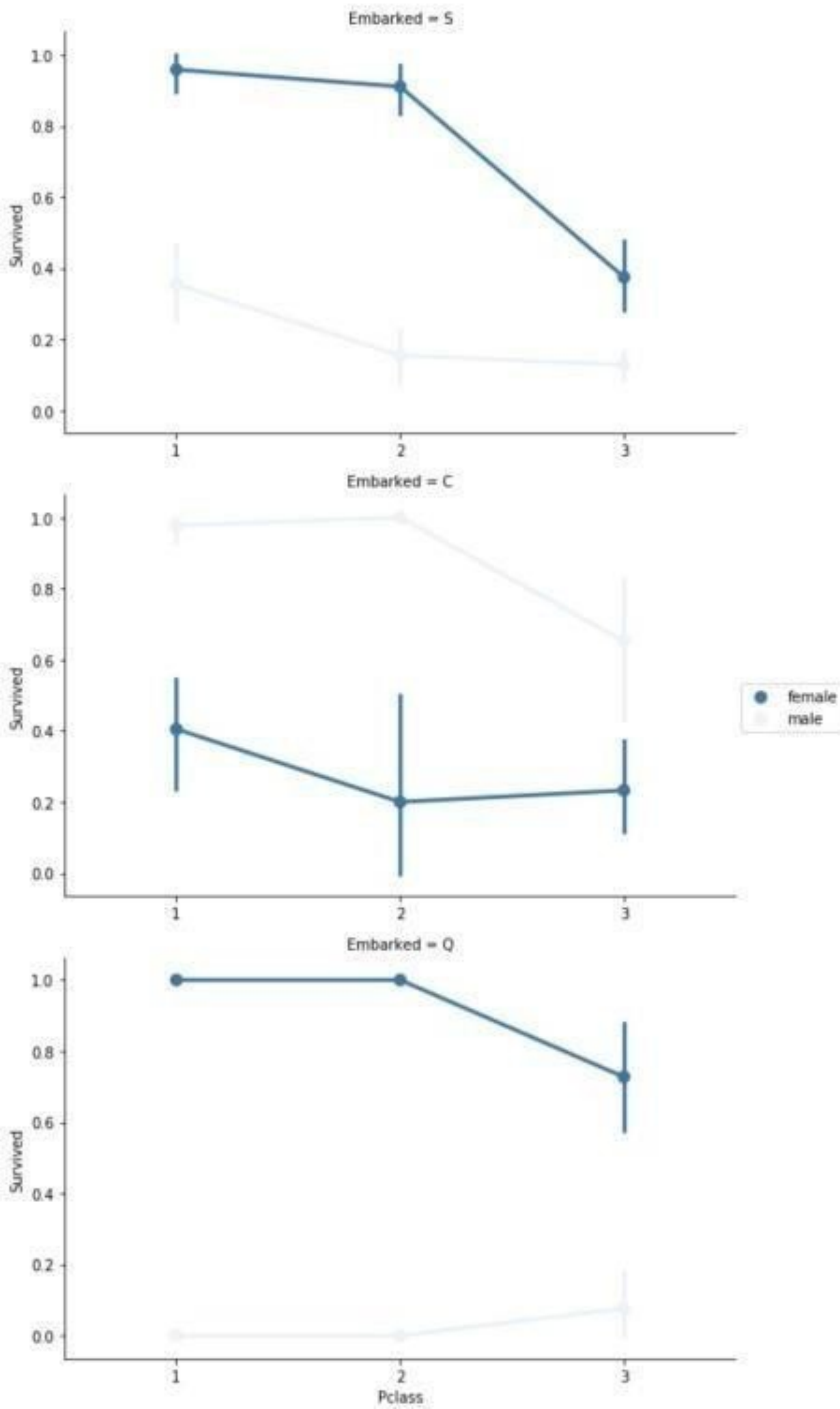
For men the probability of survival is very low between the age of 5 and 18,but that isn"t true for women. Another thing to note is that infants also have a little bit higher probability of survival.

Since there seem to be **certain ages, which have increased odds ofsurvival** and because I want every feature to be roughly on the same scale, I will create age groups later on.

3. Embarked, Pclass and Sex:

```
FacetGrid = sns.FacetGrid(train_df, row='Embarked', size=4.5,
aspect=1.6)
FacetGrid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex',
palette=None, order=None, hue_order=None )
FacetGrid.add_legend()
```

<seaborn.axisgrid.FacetGrid at 0x10ba485c0>



Embarked seems to be correlated with survival, depending on the gender.

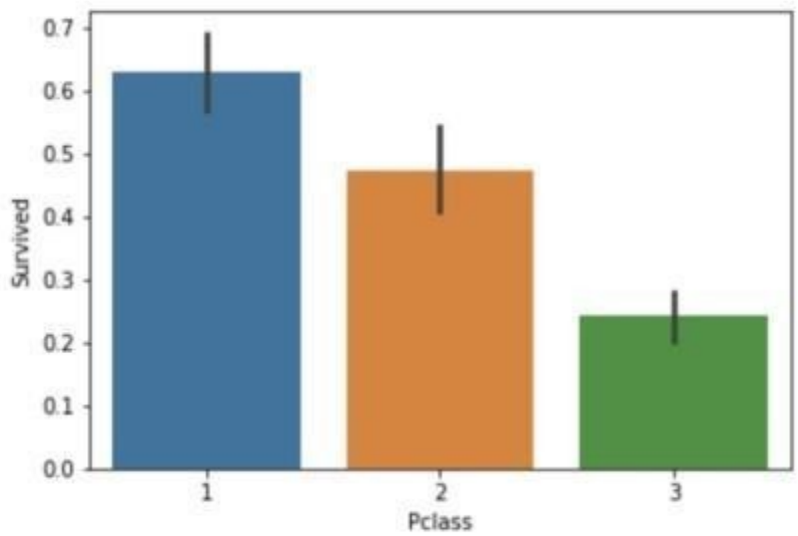
Women on port Q and on port S have a higher chance of survival. The inverse is true, if they are at port C. Men have a high survival probability ifthey are on port C, but a low probability if they are on port Q or S.

Pclass also seems to be correlated with survival. We will generate anotherplot of it below.

4. Pclass:

```
sns.barplot(x='Pclass', y='Survived', data=train_df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x10d1dc7b8>
```



Here we see clearly, that Pclass is contributing to a persons chance of survival, especially if this person is in class 1. We will create another pclassplot below.